# EXPLORING SUPERIOR FUNCTION CALLS VIA REIN-FORCEMENT LEARNING

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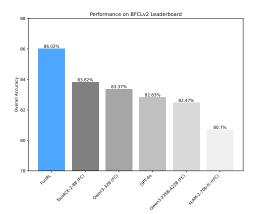
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• https://github.com/inclusionAI/AWorld • https://github.com/BingguangHao/RLFC

#### **ABSTRACT**

Function calling capabilities are crucial for deploying Large Language Models in real-world applications, yet current training approaches fail to develop robust reasoning strategies. Supervised fine-tuning produces models that rely on superficial pattern matching, while standard reinforcement learning methods struggle with the complex action space of structured function calls. We present a novel reinforcement learning framework—designed to enhance Group Relative Policy Optimization through strategic entropy-based exploration—specifically tailored for function calling tasks. Our approach addresses three critical challenges in function calling: insufficient exploration during policy learning, lack of structured reasoning in chain-of-thought generation, and inadequate verification of parameter extraction. Our two-stage data preparation pipeline ensures high-quality training samples through iterative LLM evaluation and abstract syntax tree validation. Extensive experiments on the Berkeley Function Calling Leaderboard demonstrate that this framework achieves state-of-the-art performance among open-source models with 86.02% overall accuracy, outperforming standard GRPO by up to 6% on complex multi-function scenarios. Notably, our method shows particularly strong improvements on code-pretrained models, suggesting that structured language generation capabilities provide an advantageous starting point for reinforcement learning in function calling tasks. We will release all the code, models and dataset to benefit the community.



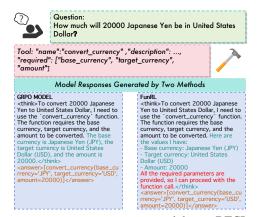


Figure 1: FunRL achieves **state-of-the-art** performance among open-source models on BFCL benchmark. FunRL effectively explores better thought processes in function call scenarios by leveraging entropy in the chain of thought. FunRL provides a more formal parameter extraction and verifies in the chain of thought.

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#### 1 Introduction

Function calling represents a pivotal advancement in the evolution of Large Language Models (LLMs), transforming them from mere text generators into highly practical and interactive tools capable of addressing real-world challenges ??. This importance stems from their unique ability to bridge the gap between an LLM's vast internal knowledge and external resources, thereby significantly enhancing functionality, accuracy, and overall utility ??. For instance, function calls enable LLMs to access up-to-date information, interact with APIs, and execute code, vastly expanding their capabilities beyond static training data ?.

Currently, the mainstream methodologies for training reasoning Large Language Models (RLLMs) primarily revolve around two major technical pathways: Supervised Fine-Tuning (SFT) on distilled reasoning trajectories and Reinforcement Learning (RL)?. However, these approaches face critical challenges in function calling scenarios. First, the **sparse reward problem** in function calling is particularly severe – a single error in parameter selection or format can render the entire function call invalid, providing limited learning signals ??. Second, the **exploration-exploitation dilemma** becomes acute when models must navigate complex tool APIs with numerous parameters, where random exploration often leads to syntactically invalid outputs ??. Third, existing methods struggle with **reasoning transparency** — while generating correct function calls is important, understanding why certain parameters were selected is equally crucial for reliability and debugging ?. Finally, the **format learning bottleneck** arises when LLMs must internalize complex API schemas with strict requirements (exact parameter names, type constraints, and hierarchical structures) while preserving their reasoning abilities, a challenge that current approaches address only superficially through post-processing rather than fundamental learning ?.

To address these limitations, we introduce FunRL, a novel reinforcement learning approach that significantly enhances LLMs' function calling capabilities through entropy-enhanced advantage estimation. Our method innovatively integrates CoT entropy into the advantage calculation, promoting more diverse reasoning paths while maintaining optimization stability. This approach is particularly crucial for function calling tasks, where models must not only generate correct function calls but also reason through complex parameter selection and verification processes. By incorporating a rigorous data preparation pipeline with AST-based evaluation and a binary reward structure that emphasizes both correctness and format compliance, FunRL ensures high-quality training data and precise feedback signals.

Our contributions are listed as follows:

- We introduce an entropy-enhanced advantage estimation method that effectively shapes the model's Chain-of-Thought process for function calling, encouraging exploration while preserving optimization direction through a carefully designed clipping mechanism.
- Our FunRL model demonstrates exceptional performance, outperforming all other opensourced models on the single-turn BFCL leaderboard. Remarkably, it also surpasses the vast majority of closed-source, ultra-large-scale models, ranking the second place in the overall leaderboard.
- We propose a comprehensive data preparation pipeline featuring dual-stage evaluation (LLM-based and AST-based) specifically designed for function calling tasks, ensuring high-quality training data through iterative refinement and strict quality control.

We will release all the code, models and dataset to benefit the community.

#### 2 Related Work

In this section, we introduce the related works, focusing on Function Call an LLM Reasoning and Reinforcement Learning.

#### 2.1 Function Call

Function calling represents a pivotal advancement in the field of LLM, transcending their traditional role of mere text generation to empower them with dynamic interaction capabilities with external

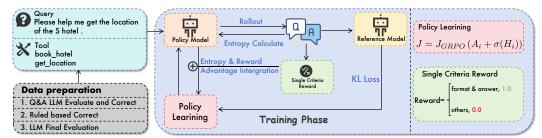


Figure 2: Overview of FunRL pipeline. The RL training process adopt a single criteria reward and use the FunRL which integrates the uncertainty of CoT to better explore the reasoning process.

environments ??. This paradigm shift enables LLMs to interface seamlessly with a vast array of tools, Application Programming Interfaces (APIs), and databases, thereby unlocking a new realm of possibilities ??. Through function calling, LLMs gain the ability to access real-time information, perform specific actions in the real world (or simulated environments), ensure the factual accuracy of their responses by consulting authoritative sources, and handle complex computations that are beyond their inherent symbolic manipulation capabilities ?.

Various approaches have been developed to facilitate and enhance function calling ??. These range from strategic prompt engineering, where specific instructions guide the LLM to recognize and utilize functions, to fine-tuning existing LLM architectures on datasets rich with function call examples ?. More specialized architectures are also emerging that are designed from the ground up with function calling in mind. Retrieval-Augmented Generation (RAG) approaches, when combined with detailed tool descriptions, enable LLMs to dynamically retrieve and employ the most appropriate tools based on the user's query ?. Furthermore, advanced agentic frameworks are being developed that allow LLMs to engage in multi-step planning and execution, making autonomous decisions about when and how to use various tools ?. However, most existing approaches primarily rely on supervised learning paradigms, which may limit the model's ability to explore diverse reasoning strategies and adapt to novel function calling scenarios ?.

#### 2.2 LLM Reasoning and Reinforcement Learning

Reinforcement Learning plays a transformative role in significantly enhancing the reasoning capabilities of LLMs, moving them beyond mere statistical pattern matching to embody more robust and sophisticated cognitive functions, such as logical deduction, complex problem-solving, and strategic decision-making ??. While LLMs inherently exhibit emergent reasoning abilities, RL provides a powerful framework for refining and amplifying these nascent capabilities. Algorithms like Proximal Policy Optimization ? and Group Relative Policy Optimization ? are commonly used to optimize the LLM's policy (its decision-making process for generating text or selecting actions) based on the received rewards ?. This enables LLMs to learn from environmental feedback in a more nuanced and effective way.

For instance, an LLM can learn to strategically utilize external tools by being rewarded for successfully leveraging them to solve problems or retrieve accurate information ??. Similarly, RL can refine dialogue interactions, allowing LLMs to engage in more coherent, contextually aware, and goal-oriented conversations ?. Beyond just improving response quality, RL helps LLMs develop a deeper understanding of task objectives and the underlying logical structure of problems ??. The integration of RL, especially with human-in-the-loop feedback, is thus fundamental to unlocking the full potential of LLMs as truly reasoning and problem-solving AI systems ??. Nevertheless, current RL approaches for function calling often struggle with balancing exploration and exploitation, particularly when the model needs to generate both reasoning steps and precise function calls ?. Our FunRL method addresses this challenge by incorporating Chain-of-Thought entropy into the advantage calculation, encouraging the model to explore diverse reasoning paths while maintaining stable optimization for accurate function calling.

#### 3 Preliminaries

This section formally defines the function calling task and introduces Group Relative Policy Optimization (GRPO), the foundational reinforcement learning algorithm upon which our method is built?

#### 3.1 TASK DEFINITION

#### 3.2 GRPO

Group Relative Policy Optimization (GRPO) serves as an efficient alternative to Proximal Policy Optimization (PPO), leveraging Generalized Advantage Estimation (GAE) without the need to learn a separate value function ???. Instead, it estimates advantages by using the average reward across multiple sampled outputs for the same query as a baseline, followed by normalization. For a set of rewards  $\{r_1, \ldots, r_S\}$  corresponding to S rollouts for a given query, the advantage  $A_i$  for rollout  $o_i$  with reward  $r_i$  is computed as:

$$A_i = \frac{r_i - \operatorname{mean}(\{r_1, \dots, r_S\})}{\operatorname{std}(\{r_1, \dots, r_S\})}.$$
 (1)

The policy is optimized by maximizing a clipped surrogate objective:

$$\mathcal{J} = \mathbb{E}_{q \sim \mathcal{D}, o \sim \pi_{\text{old}}(O|q)} \sum_{t=1}^{S} \left[ \min \left( \rho_{t} \hat{A}_{t}, \text{clip} \left( \rho_{t}, 1 - \varepsilon, 1 + \varepsilon \right) \hat{A}_{t} \right) - \beta \text{KL}(\pi \| \pi_{\text{ref}}) \right], \tag{2}$$

where  $\rho_t = \frac{\pi(o_t|q,o_{< t})}{\pi_{\text{old}}(o_t|q,o_{< t})}$  is the likelihood ratio between the current policy  $\pi$  and the old policy  $\pi_{\text{old}}$ ,  $\hat{A}_t$  denotes the estimated advantage, and  $\varepsilon$  and  $\beta$  are hyperparameters controlling the clipping range and KL divergence penalty, respectively. This formulation promotes stable policy updates while encouraging alignment with a reference policy  $\pi_{\text{ref}}$ .

#### 4 METHOD

In this section, we describe our proposed FunRL method in details, beginning with data preparation, followed by the design of the reward function, and culminating in the core algorithmic innovations.

#### 4.1 DATA PREPARATION

Our data preparation pipeline is engineered to produce high-quality samples for reinforcement learning in function calling tasks. For each initial input tuple (q,T,g)—where q denotes the user query, T represents the set of available tools, and g is the reference answer—the data undergoes a rigorous two-stage evaluation process, as depicted in Figure 3.

The pipeline consists of the following evaluations:

1. **LLM Evaluation and Correction:** An initial assessment is conducted using a large language model (LLM) to evaluate the query-tool-answer tuple. If discrepancies or errors are

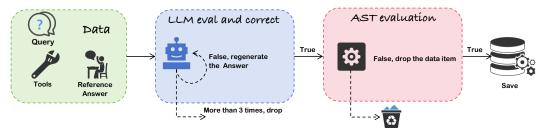


Figure 3: Implementation of the data cleaning pipeline for reinforcement learning in function calling. We begin with LLM-based evaluation and correction, followed by AST evaluation. Data is retained only after passing all stages or discarded after three regeneration attempts.

detected, the LLM regenerates the answer to rectify them. To maintain data quality, a strict dropout mechanism is enforced: samples are discarded if regeneration exceeds three attempts. This stage yields a binary outcome, denoted as  $Eval_{LLM}(q,T,g) \in \{\text{True}, \text{False}\}$ .

2. **Abstract Syntax Tree (AST) Evaluation:** Following a successful LLM evaluation, an AST-based assessment is performed on the reference answer. A sample is discarded if: (i) the query cannot be addressed by any tool in T, but g parses as a valid tool call via AST; or (ii) the query requires a tool call, but g is free-form text that fails AST parsing. This stage also produces a binary result, denoted as  $Eval_{AST}(q,T,g) \in \{\text{True}, \text{False}\}$ .

Only samples that pass both evaluations (i.e.,  $Eval_{AST}(q,T,g) \wedge Eval_{LLM}(q,T,g)$ ) are retained in the database. For our experiments, we refined a subset of the xLAM dataset, yielding 58k high-quality samples ?. These are formatted in ShareGPT style and converted to Parquet for integration with the Verl RL framework ?.

#### 4.2 REWARD DESIGN

Building on the prepared data, we adapt the xLAM dataset for reinforcement learning by designing a straightforward yet effective reward function. For a given query q with reference answer g, the model's generated answer g is evaluated as follows: If g involves a tool call, g is deemed correct only if it parses successfully via AST, exactly matches g, and adheres to the required format. Conversely, if g does not involve a tool call, g is correct only if it fails AST parsing (indicating free-form text) and complies with the format. In all cases, failure to meet the format—specifically, the structure g in the square g is an incorrect classification.

The reward is thus defined as:

$$r(c_1, \cdots, f_L) = \begin{cases} 1, & \text{if format and answer are correct} \\ 0, & \text{otherwise.} \end{cases}$$
 (3)

This binary reward emphasizes the holistic integrity of the output, ensuring not only semantic accuracy but also precise structural compliance, which is critical for downstream processing. For non-tool-calling scenarios, the AST failure condition implicitly confirms that the response is appropriately textual and avoids spurious tool invocations.

#### 4.3 FunRL

To enhance exploration in the Chain-of-Thought (CoT) reasoning process within the RL framework, our FunRL method incorporates CoT entropy into the advantage calculation. For a query q and a set of rollouts  $O = \{o_1, \ldots, o_S\}$ , where each  $o_i = \{c_1, \ldots, c_W, f_1, \ldots, f_L\}$  (with  $c_j$  as CoT tokens and  $f_k$  as final answer tokens), the token-level entropy is computed as:

$$E = -\sum_{i=1}^{S} \sum_{j=1}^{W} \pi(c_{ij} \mid q, T) \log \pi(c_{ij} \mid q, T).$$
(4)

This entropy term is then scaled and clipped before integration into the advantage function:

$$A_t^{\text{new}} = A_t + \min\left(\lambda E, \frac{|A_t|}{\alpha}\right),\tag{5}$$

Models	Non-Live AST Acc	Live Acc	Overall					
Close-Sourced Models								
o1-2024-12-17 (Prompt)	85.67	80.63	83.15					
o3-mini-2025-01-31 (Prompt)	86.15	79.08	82.62					
GPT-4o-2024-11-20	86.81	78.85	82.83					
GPT-4.5-Preview-2025-02-27	86.12	79.34	82.73					
GPT-4.1-2025-04-14 (FC)	85.42	79.92	82.67					
Gemini-2.0-Flash-001 (Prompt)	84.48	81.39	82.94					
Gemini-2.5-Pro-Preview-05-06 (FC)	65.35	74.59	69.97					
Grok-3-beta (FC)	63.96	77.25	70.61					
Open-Sourced Models								
Llama-4-Maverick-17B-128E-Inst-FP8	86.65	58.55	72.60					
Llama-3.3-70B-Instruct	85.08	62.67	73.88					
Llama-3.2-3B-Instruct	80.56	55.80	68.18					
Qwen3-235B-A22B (FC)	87.90	77.03	82.47					
Qwen3-32B (FC)	88.90	77.83	83.37					
Qwen2.5-Coder-7B-Instruct	84.08	69.78	76.93					
Qwen2.5-7B-Inst(ToolRL)?	86.17	74.90	80.54					
xLAM-2-70b-fc-r (FC) ?	88.44	72.95	80.70					
ToolACE-2-8B (FC) ?	87.58	80.05	83.82					
TooL-N1-7B( $xLAM$ )?	87.77	76.24	82.01					
Ours								
Llama-3.2-3B-Instruct (FunRL)	79.75	74.77	77.26					
Qwen2.5-Coder-7B-Instruct (FunRL)	90.40	81.64	86.02					

Table 1: Performance on BFCL (last updated June 14, 2025), with all metrics calculated using the official script. The best result within each category is highlighted in **bold**.

where  $\lambda>0$  is a scaling factor for entropy weighting, and  $\alpha>1$  governs the clipping threshold. The clipping via  $\frac{|A_t|}{\alpha}$  prevents the entropy adjustment from inverting the sign of the original advantage  $A_t$ , thereby maintaining the optimization direction while fostering diverse CoT explorations—particularly when  $A_t$  is small ???. This mechanism strikes a balance between directed learning and exploratory reasoning, enhancing the model's robustness in function calling tasks.

#### 5 EXPERIMENT

The experiments in this paper are divided into three parts. The first part elaborates on the experiment settings. The main results of FunRL are illustrated in the second part. In the third part, we adopt a comprehensive ablation study.

#### 5.1 EXPERIMENT SETTING

In this subsection, we describe the experimental setup including datasets, hyperparameters, base models, and evaluation metrics.

**Training Data.** We conduct experiments using a cleaned version of the xLAM dataset ?. The data cleaning process employs GPT-4.1-2025-04-14 for first-stage evaluation. The processed data is formatted in ShareGPT format and converted to Parquet format for compatibility with the Verl RL framework ?. Table 2 summarizes the data statistics after each processing stage.

Implementation Details. We train models for 8 epochs with a learning rate of  $1\times 10^{-6}$  and temperature of 0.7. Training is performed on 8 H200 GPUs with a batch size of 1,024, using 8 rollouts and reserving 10% of data for validation. We set the KL coefficient to 0.001, entropy coefficient to 0, and maximum response length to 8,192 tokens. The hyperparameters  $\lambda$  and  $\alpha$  are set to 2 and 0.1 respectively, based on preliminary experiments. Given the strong instruction-following capa-

<b>Processing Stage</b>	Samples			
Original xLAM	60,000			
After LLM Evaluation	59,641			
After AST Evaluation	58,759			

Table 2: Data statistics in two-stage preparation.

bilities of Qwen-Coder-Instruct-7B, we directly apply reinforcement learning without cold start ??. This approach yields competitive performance, as demonstrated in our results. During training, the model develops stable reasoning patterns, including targeted parameter extraction and validation at tool call generation points. These emergent behaviors indicate that our training approach effectively enhances logical reasoning for tool calling tasks.

**Base Models.** To evaluate the generalizability of FunRL, we experiment with diverse base models: Llama-3.2-3B-Instruct ?, Qwen-2.5-Coder-Instruct-7B and Qwen-2.5-Instruct-7B ??, and DeepSeek-Coder-6.7B-Instruct ?.

**Baselines.** We compare against state-of-the-art function calling models of similar scale: Toolace-8B ?, xLAM-2-8B ?, ToolRL-7B ?, and Tool-N1-7B ?. We also include GPT-4o ? as a reference for general-domain performance.

**Evaluation.** We evaluate single-turn tool calling performance using the Berkeley Function Calling Leaderboard (BFCL) v2 ?. Our evaluation covers both the Non-live subset (synthetic data) and Live subset (real-world scenarios), with accuracy as the primary metric.

#### 5.2 Main Result

In this subsection, we will introduce the main result and a comprehensive analysis.

**Evaluation on BFCL.** As shown in Table 1, our models, particularly Qwen2.5-Coder-7B-Instruct (FunRL), demonstrate superior performance across all evaluated metrics. It achieves the highest Overall accuracy at 86.02%, significantly outperforming both close-sourced and other open-sourced models. For instance, it surpasses the most close-sourced model, GPT-4o-2024-11-20 (Overall: 82.83%), by over 3 percentage points. Compared to other leading open-sourced models like ToolACE-2-8B (FC) (Overall: 83.82%) and Qwen3-32B (FC) (Overall: 83.37%), Qwen2.5-Coder-7B-Instruct (FunRL) maintains a notable lead of more than 2 percentage points.

Furthermore, Qwen2.5-Coder-7B-Instruct (FunRL) achieves the highest Non-Live AST Acc at 90.40%. This is a substantial improvement over the previous (Qwen3-32B (FC) at 88.90% and GPT-4o-2024-11-20 at 86.81%). In terms of Live Acc, Qwen2.5-Coder-7B-Instruct (FunRL) also leads with 81.64%, exceeding the most models, Gemini-2.0-Flash-001 (Prompt) (81.39%), and significantly outperforming most open-sourced models.

For Llama-3.2-3B-Inst (FunRL), it achieves a remarkable 18.97 percentage point increase in Live Acc, indicating that FunRL approach significantly enhances the model's performance in real-time or dynamic scenarios. This strong gain makes Llama-3.2-3B-Inst (FunRL) a much more robust and effective model compared to its base version for the tasks evaluated.

Comparison between FunRL and pure GRPO. As revealed in Figure 4, we use identical training sets, hyperparameters, and base models, we conduct comparative experiments on Qwen2.5-Coder-7B-Instruct by using GRPO and FunRL. In the Non-Live section, the Base model started at 84.04%, with GRPO improving it to 89.54%. However, FunRL further refined this, achieving the highest accuracy of 90.40%, marking a consistent and notable uplift with each successive optimization method. The trend is even more pronounced in the Live section. Starting from a Base accuracy of 69.78%, GRPO elevated it to 78.58%. Crucially, FunRL demonstrated its strongest impact here, pushing the Live Acc to 81.64%. This substantial improvement, particularly in Live Section, where real-time performance is critical, highlights that FunRL is not just incrementally better but provides a significant boost in dynamic operational environments compared to the GRPO method.

**Visualization of Learning Curves.** We present the visualized learning curves in Figure 5, including the KL divergence and average reward during the training steps. The KL divergence and average reward shown in Figure 5 (a) and Figure 5 (b) demonstrate continuous improvement and stabiliza-

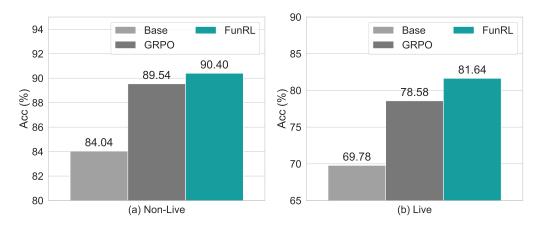


Figure 4: Performance of Base Model, FunRL and GRPO on two diverse sections of BFCL trained on Owen2.5-Coder-7B-Instruct.

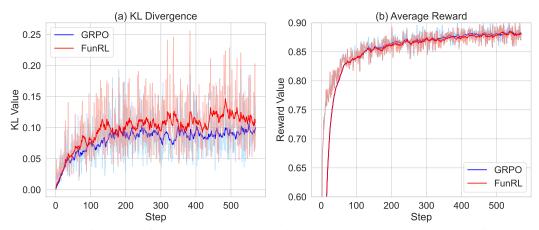


Figure 5: Learning curves for FunRL and GRPO during training steps. We report the KL divergence and average reward. FunRL corresponds a larger KL divergence, which is driven by the entropy to explore a better thinking pattern.

tion, indicating that the model achieves stable learning and exploration under the training settings. It's worth noting that in Figure 5 (a), during the middle and later stages of training, the KL divergence of FunRL is significantly higher than that of GRPO. This observation suggests that the model trained by FunRL deviates further from the base model, implying that introducing the entropy of the chain of thought in the advantage computation of reinforcement learning allows the model to better explore a thinking pattern suitable for function calling scenarios.

#### 5.3 ABLATIONS

Here, we conduct further ablation experiments to compare the performance of FunRL and GRPO on different base models.

**Qwen2.5-Coder-7B-Instruct & Qwen2.5-7B-Instruct.** In Figure 6, we show the performance of GRPO and FunRL trained on two base models, Qwen2.5-Coder-7B-Instruct and Qwen2.5-7B-Instruct. We discover that, for the Base performance, Qwen2.5-7B-Instruct (77.3%) initially shows a slight edge over Qwen2.5-Coder-7B-Instruct (76.91%), indicating a very similar baseline capability between the two. However, when the GRPO optimization is applied, Qwen2.5-Coder-7B-Instruct achieves 84.06%, which is marginally lower than Qwen2.5-7B-Instruct's 84.11%. This suggests that GRPO provides a comparable uplift to both models, maintaining their close performance proximity. The most significant distinction arises with the application of FunRL. Qwen2.5-Coder-7B-Instruct, with FunRL, reaches 86.02% accuracy, outperforming Qwen2.5-7B-Instruct, which achieves 85.15% with FunRL. This indicates that while both models benefit substantially from

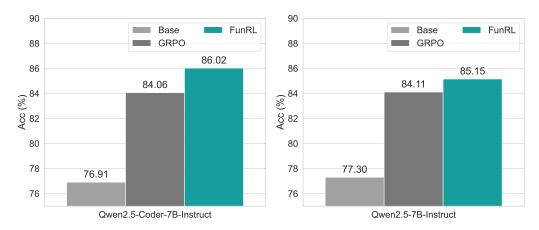


Figure 6: Performance of FunRL and GRPO on BFCL trained on Qwen2.5-Coder-7B-Instruct and Qwen2.5-7B-Instruct.

FunRL, Qwen2.5-Coder-7B-Instruct ultimately reaches a higher peak performance on the BFCL task when optimized with FunRL. This suggests that its pre-training on coding related tasks, combines with the FunRL method, has an advantage in function calling, potentially due to the discovery of a better thinking pattern.

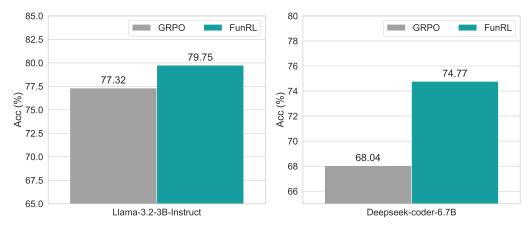


Figure 7: Performance of FunRL and GRPO on BFCL trained on Llama-3.2-3B-Instruct and Deepseek-coder-6.7B.

Other Series Models. To further validate the universality and effectiveness of our method, we conducted additional experiments on Llama-3.2-3B-Instruct from the Llama series and Deepseek-coder-6.7B from the Deepseek series. The results are presented in Figure 7. We find that for the Llama-3.2-3B-Instruct model, GRPO achieves an accuracy of 77.32%. FunRL, however, demonstrates a clear improvement, boosting the accuracy to 79.75%. This represents a gain of 2.43 percentage points by using FunRL over GRPO, indicating that for this specific Llama model, FunRL provides a more effective optimization. A similar trend of FunRL outperforming GRPO is observed with the Deepseek-coder-6.7B model, though the baseline accuracy for GRPO is lower. Here, GRPO yields an accuracy of 68.04%. FunRL again shows a significant uplift, increasing the accuracy to 74.77%. This translates to a more substantial improvement of 6.73 percentage points when using FunRL compared to GRPO. The larger performance gap between FunRL and GRPO on Deepseek-coder-6.7B and Qwen2.5-Coder-7B-Instruct model suggests that FunRL is particularly beneficial for models that pre-trained with code tasks.

#### 6 DISCUSSION

Our results demonstrate FunRL's significant leap in function calling for LLMs. Integrating CoT entropy into advantage calculation fosters robust reasoning and precise parameter extraction, evidenced by improved accuracy on the BFCL. The higher KL divergence confirms FunRL's broader exploration of thinking patterns, crucial for navigating complex queries. This finding validates our hypothesis that encouraging exploration in the reasoning space leads to more robust function calling capabilities. Our rigorous two-stage data pipeline and binary reward function further ensure high-quality learning. The LLM-based evaluation followed by AST validation creates a robust filtering mechanism that eliminates noisy training samples, which proves critical for stable RL training. Notably, FunRL excels with code-pretrained models, suggesting their structured language understanding provides an advantageous foundation. The performance gap between Qwen2.5-Coder-7B-Instruct and Qwen2.5-7B-Instruct under FunRL (86.02% vs 85.15%) highlights how code-oriented pretraining creates beneficial inductive biases. This synergy of pre-training and targeted RL is a promising avenue for future AI agents.

#### 7 CONCLUSION

We present FunRL, a novel reinforcement learning framework that markedly enhances LLM function calling by incorporating Chain-of-Thought entropy into GRPO. Our method tackles key challenges like exploration, structured reasoning, and parameter verification through a rigorous two-stage data pipeline and a precise binary reward signal. By encouraging diverse reasoning paths while maintaining optimization stability, FunRL enables models to develop more sophisticated parameter extraction strategies. FunRL achieves **state-of-the-art** performance among open-source models on the BFCLv2, with Qwen2.5-Coder-7B-Instruct (FunRL) reaching 86.02% overall accuracy, outperforming GRPO by up to 6%. The significant improvements on the Live subset demonstrate FunRL's effectiveness in real-world scenarios. FunRL represents a significant advancement towards building more intelligent and reliable LLMs for real-world tool interaction.

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### A Q & A TEMPLATE

The following Q & A Template, with its predefined set of instructions, guidelines, and constraints, plays a pivotal role in standardizing the behavior, output format of the model being trained and evaluated. It ensures that during the training phase, the model learns in a consistent manner aligned with the desired objectives, and during the BFCL evaluation, the performance is generated under a unified set of rules.

#### Q & A Template

#### System Prompt

You are an expert in composing functions. You are given a question and a set of possible functions. Based on the question, you will need to make one or more function/tool calls to achieve the purpose. If none of the function can be used, point it out. If the given question lacks the parameters required by the function, also point it out. You should only return the function call in tools call sections.

# Tool

Here is a list of functions in JSON format that you can invoke: {functions}

In each action step, you MUST:

- 1. Think about the reasoning process in the mind and enclosed your reasoning within <think></think> XML tags.
- 2. Then, provide a function call with function names and arguments within <an-swer></answer> XML tags. i.e., <answer> [func\_name1(params\_name1=params\_value1, params\_name2=params\_value2...), func\_name2(params)] </answer>
- 3. Make sure both the reasoning and the tool call steps are included together in one single reply.

A complete reply example is: <think>reasoning process here</think> <answer>answer here</answer>

Please make sure the type of the arguments is correct and reject to answer if the function can not solve the user's question.

#### Answer

<think>reasoning process here</think>
<answer>answer here</answer>

#### A.1 SUPPLEMENTARY CASE

By giving the same Question and Function, we show the thinking processes and answers of Qwen-Coder-7B-Instruct trained by FunRL and GRPO. It allows for a clear observation of how each training paradigm influences the model's reasoning steps—such as the sequence of logic application, the depth of problem decomposition, and the handling of ambiguous or complex elements within the Question. By maintaining the consistency of the Question and Function, we eliminate external variables that could otherwise obscure the impact of the training methods, thereby facilitating a focused evaluation of how FunRL and GRPO shape the model's cognitive abilities and output characteristics in the context of solving the given task.

	Non-Live			Live			Overall				
Models	Simple	Multiple	Parallel	Parallel Multiple	Simple	Multiple	Parallel	Parallel Multiple	Non-live	Live	Overall
GPT-4o	79.42	95.50	94.00	83.50	84.88	79.77	87.50	75.00	88.10	79.83	83.97
GPT-4o-mini	80.08	90.50	89.50	87.00	81.40	76.73	93.75	79.17	86.77	76.50	81.64
GPT-3.5-Turbo-0125	77.92	93.50	67.00	53.00	80.62	78.63	75.00	58.33	72.85	68.55	70.70
Gemini-2.0-Flash-001	74.92	89.50	86.50	87.00	75.58	73.12	81.25	83.33	84.48	81.39	82.94
DeepSeek-R1	76.42	94.50	90.05	88.00	84.11	79.87	87.50	70.83	87.35	74.41	80.88
Llama3.1-70B-Inst	77.92	96.00	94.50	91.50	78.29	76.16	87.50	66.67	89.98	62.24	76.11
Llama3.1-8B-Inst	72.83	93.50	87.00	83.50	74.03	73.31	56.25	54.17	84.21	61.08	72.65
Qwen2.5-7B-Inst	75.33	94.50	91.50	84.50	76.74	74.93	62.50	70.83	86.46	67.44	76.95
xLAM-2-70b-fc-r (FC)	78.25	94.50	92.00	89.00	77.13	71.13	68.75	58.33	88.44	72.95	80.70
ToolACE-8B (FC)	76.67	93.50	90.50	89.50	73.26	76.73	81.25	70.83	87.54	78.59	82.57
Hammer2.1-7B (FC)	78.08	95.00	93.50	88.00	76.74	77.4	81.25	70.83	88.65	75.11	81.88
Tool-N1-7B	77.00	95.00	94.50	90.50	82.17	80.44	62.50	70.83	89.25	80.38	84.82
FunRL	78.58	95.50	95.50	92.00	80.23	79.68	87.50	83.33	90.40	81.64	86.02

Table 3: The evaluation details on BFCL benchmark (last updated June 14, 2025), with all metrics calculated using the official script.

#### Case Study

#### **User Query**

Find the ranking of LA Lakers in the NBA 2021 regular season.

["name": "get\_team\_rank", "description": "Get the team ranking in a sports league based on season and type.", "parameters": "type": "dict", "properties": "team\_name": "type": "string", "description": "The name of the sports team.", "league": "type": "string", "description": "The name of the league in which the team competes.", "season": "type": "string", "description": "The season for which the team's ranking is sought.", "type": "type": "string", "description": "Type of the season: regular or playoff.", "enum": ["regular", "playoff"], "required": ["team\_name", "league", "season", "type"]]

## Answer

#### **FunRL**

<think>To find the ranking of the LA Lakers in the NBA 2021 regular season, I need to use the 'get\_team\_rank' function. The function requires the team name, league, season, and type of the season. The parameters provided are:

- "team\_name": "LA Lakers"
- "league": "NBA" "season": "2021"
- "type": "regular"

These parameters match exactly with what the function expects.</think> <answer>[get\_team\_rank(team\_name="LA Lakers", league="NBA", season="2021", type="regular")]</answer>

#### **GRPO**

<think>The question is asking for the ranking of LA Lakers in the NBA during the 2021 regular season. The function 'get\_team\_rank' can be used to get the team ranking based on the provided parameters.</think>

<answer>[get\_team\_rank(team\_name='LA Lakers', league='NBA', season=2021', type='regular')]</answer>

#### **EVALUATION DETAILS**

We evaluate our model on BFCL benchmark, where FunRL attains superior performance with scores of 90.40% and 91.65% on non-live and live section. The results surpass all similar scale models and achieve great enhancement on Parallel and Parallel Multiple subsection, which indicates that our model has achieved excellent tool-calling capabilities under complex queries, the evaluation details are shown in Table. 3.